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3 Individual publication productivity as a social position effect in academic and industrial research units

Karin D. Knorr, Roland Mittermeir, Georg Aichholzer, and Georg Waller
Institute for Advanced Studies, Vienna

1. Productivity and stratification in science

Throughout the development of the sociology of science, the study of normal scientific activity has focused on the general stratification and communication system in science. This seems to affect all scientific fields and manifests itself most clearly in the skewed distributions of productivity and rewards. There have been productivity studies on scientists of a variety of disciplines, including, among others, physiologists (Meltzer, 1956), psychologists (Clark, 1957), sociologists (Meltzer, 1949; Axelson, 1959; Babchuk and Bates, 1962; Clemente, 1974), medical researchers (Ben-David, I960), biologists and political scientists (Crane, 1965), psychometricians (Thomasson and Stanley, 1966), physicists (Cole and Cole, 1967, 1968; Gaston, 1969; Cole, 1970; Zuckerman and Merton, 1971) and chemists (Hagstrom, 1971; Blume and Sinclair, 1973a, b). Other studies, like that of Pelz and Andrews (1966), covered a wide variety of scientists from different specialities and disciplines.

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Although many of the findings reported in this body of literature are, as Kaplan (1964: 967) has noted, ambiguous and often contradictory, there seems to be an emergent consensus that scientific activities are highly stratified and elitist in nature. For example, as has been known since Lotka (1926), only a small and select minority of scientists produce the bulk of scientific papers published in the literature. Price (1963) suggested that the square root of the population of scientists produces 50% of scientific discoveries. Merton (1968) proposed the *Matthew effect*, which asserts that those who are well known receive more credit for their work than those who are less well known ("unto everyone that has shall be given" according to the Gospel of Saint Matthew, Chapter 25, Verse 29).

Various aspects of social stratification in the scientific community have recently been examined by Cole and Cole, using citation counts as a measure of the quality of scientific output. Their findings suggest that scientists located in the top stratum of academic science predominantly cite the discoveries produced by other members of the same elite stratum, and furthermore that even members of the lowest stratum disproportionately cite the work produced by distinguished scientists, although to a lesser extent than those who are themselves members of the scientific elite (Cole, 1970). Additionally, according to Cole and Cole (1968), quality of work, as measured by citations received and rank of department, accounts for most of the variance in the "visibility" or reputation of a scientist.

Those results, as well as some of the earlier ones by Crane (1965) as to the high correlation between academic setting and both productivity and recognition, seemingly lend themselves to the interpretation that greater ease of publication and hence higher visibility and reputation stem from having high levels of individual or academic status. Rewards received not so much as a consequence of the individual's general contribution to science but rather as the result of the preferential citing of the eminent or of the appointment of the eminent must, as noted by Blume and Sinclair (1973a: 134), truly be called unmerited. However, Zuckerman and Merton (1971) found that the formal control mechanisms of science, such as reviewing and publication processes, are *not* affected by status differentials of the authors or papers submitted. The findings of Hargens and Hagstrom (1967) and Hagstrom (1971) support those conclusions: Hargens and Hagstrom showed that status does not relate to productivity on the individual level, although it does on the aggregate. In addition, Hagstrom (1971) claimed that no sociological variables either singularly or in combination account for much of the differences in productivity.

If status does not confer easier access to publication and if ascriptive factors are not primarily relevant for the recognition accorded the like contributions of two unlike scientists, this raises the question as to how the large publication differentials between higher- and lower-rank scientists can be explained. The above studies provide no simple explanation for this differential productivity. Zuckerman (1970) showed that age is associated with rank and hence with productivity, and Pelz and Andrews (1966) report a continuing increase of productivity with age up to the early or late 40s (varied for different types of laboratories and education), with a renascence of productivity manifesting itself in a second peak of the age curves about 10 to 15 years later. These findings, in addition to standing in distinct contrast to data presented by Lehmann (1953, 1958, I960) as to a continuing decline of major scientific contributions from the late 30s onward, also do not lend themselves to an easier understanding of productivity differentials. If age and professional experience are important explanatory variables, how does it come about that the average productivity in a unit of time (as measured by the number of written products within the last 3 or 5 years and hence adjusted for the accumulating effects of age) rises so steadily not only during the first years of a professional career-where initial lack of research experience alone might provide an adequate explanation - but rather for 15 to 20 years after graduation?

This chapter attempts to supply some further details as to how productivity differences associated with rank or age can be understood by extending the above research to include intraorganizational variables as a source of explanation. As noted by Whitley (1976), scientists may be affected more by organizational settings and structures than is usually emphasized in stratification studies. If one were to take the idea of science as a highly stratified system one step further and apply it to the system of a single organization, this would lead one to expect scientific productivity to be associated with the status or position a scientist holds in the formal or informal scientific hierarchy of the organization. The question as to why higher position should confer greater productivity can then be answered by pointing to the differential resources and task structures associated with different levels. It is our contention that higher positions-except for the extreme case where the scientist moves out of science altogether-provide better opportunities for publication, for the simple reason that a scientist's publication capacity is multiplied by the task force he or she supervises and by the project (and other) money to which he or she gains access (compare Mullins, 1975).

More explicitly, one could reason that status in general might not confer greater ease of publication in the simple sense of intriguing referees and publishing companies toward publication of whatever is submitted by a high-status scientist, but rather that status may confer greater ease of production by opening up channels or resources not accessible to those in low positions. The relationship between age and productivity found in previous studies would then have to be discussed in the light of the association between a scientist's age and the position he or she has attained in his organizational environment. Because age and the level of supervisory position are presumably highly correlated in bureaucratic organizations (like universities or academies of science), it may well be position and the resources and task structure associated with it-and not so much mere chronological age or professional experience-that account for most of the variance in productivity.

At this point, sufficient research has been done in the present study to outline the contours of a model that uses the intraorganizational position of a scientist as a key element associated with productivity. Because productivity differences are linked to social mechanisms, the model can be interpreted in terms of the *accumulative advantage* hypothesis (e.g., Allison and Stewart, 1974).

Before describing the model mentioned above (which will be represented within a structural equation approach), this chapter proceeds to examine the relationship between age and productivity, and to explore whether age can be considered a proxy for the position a scientist has attained in a research organization. Furthermore, the relationship between years spent in research and productivity, and the nature of task structures that may be conducive to a high quantity of output, will be analyzed. Finally, the social-position model of individual publication productivity will be supplemented by some details as to how group productivity is related to individual productivity and what additional factors have to be taken into account when group output is examined.

2. Data

The data presented in this chapter are drawn from the International Comparative Study on the Organization and Performance of Research Units. The analyses focus on the professional-level members (unit heads and staff scientists) in three types of units:

units working in the natural sciences and located in academic organizations, units working in the technological sciences[1] and located in academic organizations, and units working in the technological sciences and located in industrial organizations. These three types of units were chosen as relevant subgroups for which all analyses were conducted separately. This decision was based on a typological analysis of quantitative and qualitative performance measures in different disciplines and types of institutions in the present data set (Cole, 1978; Chapter 13 of this volume), which showed that performance patterns differed markedly among the above settings but that no significant gain was made by looking at single disciplines separately, for example, at academic chemistry. Most of the analyses in this chapter examine data from individual respondents; however, near the end of the chapter some unit-level results are presented. All analyses use data that have been aggregated across the six countries that participated in the study.

3. Measurement of productivity

In order to examine scientific productivity in relation to stratification or organizational variables, a variety of approaches to the construction of operational indicators of performance have been used in the literature. As noted by Blume and Sinclair (1973a), the only valid assessment of a contribution to science must come from within the respective speciality, for only members of a speciality are sufficiently competent to judge the significance of a scientific contribution to their field. Despite the fact that most social scientists working on scientific productivity have agreed on the ideal of such a measurement of scientific quality, in practice many have gone on to use a simple counting of published papers as the most viable way of dealing with the problem (e.g., Coler, 1963; Price, 1963; Crane, 1965; Gaston, 1969). Meltzer and Salter (1962; 354) note some of the objections that might be raised against such a productivity measure: a co-author is given the same amount of credit as a full author, a short paper is counted the same as a long one, no distinction is made between poor and excellent products, no difference can be distinguished between highly original work and the repetition of old ideas, and the benefits of having written the product may be attributed to those who only exploited the ideas or research work of others.

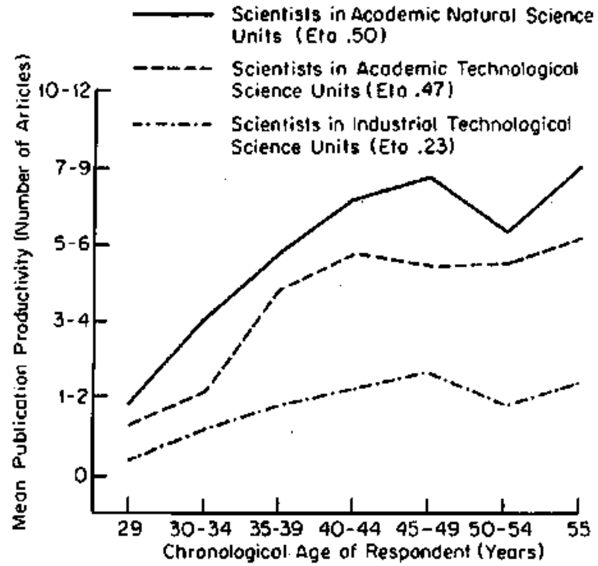
Despite the plausibility of those arguments, fairly consistent evidence has come up in the literature for a high or moderate correlation between the sheer volume of a scientist's published papers and the quality of his or her work, as measured by ratings of competence by peers or citation counts (see Meltzer, 1949, 1956; Dennis, 1954; Clark, 1957; Pelz and Andrews, 1966; Thomasson and Stanley, 1966; Cole and Cole, 1967, 1971; and Blume and Sinclair, 1973a,b).[2] The conclusion seems to be that where citation counts are not readily available-as in the case of a study including countries not adequately or not at all represented in the science citation index —publication counts are roughly adequate indicators of the significance of a scientist's work (cf. Cole and Cole, 1971: 26).

Although our data allow for the assessment of the rated quality[3] of the scientific work' of our respondents in addition to its quantity, they do not include a measure of citation counts for the reason mentioned above. In the present examination, we shall rely almost exclusively on the quantitative measurement of research productivity. This will enable us to relate our results to findings in the existing literature more directly than would be the case if results were based on the rated performance measures.

Following a frequent procedure (e.g., Pelz and Andrews, 1966; Hagstrom, 1967; Gaston, 1969), we took as our indicator of "publication productivity" the self-reported number of papers a respondent had published in scientific journals in connection with his or her work in the research unit. In order to eliminate the cumulative effect of sheer professional age, respondents were to list only the papers published during the last three years. Where the Iisrel technique has been used (below in this chapter), the number of scientific books published in the same time period has been included in the analysis as a second indicator of publication productivity, justified by a sufficiently high correlation between both kinds of output.[4]

4. Age, professional experience, and productivity

Earlier work to which we have referred above suggested a somewhat curvilinear relationship between a scientist's age and his or her scientific productivity. Whereas Lehmann's results show a continuous decline of productivity after achievement peaks around the late 30s (depending on discipline), Pelz and Andrews generally report the peak at a later age, in the 40s, followed by a 10 to 15 years sag with a comeback in the 50s. Our data offer a partial verification of those results: Exhibit 3.1 shows the mean production of papers by scientists in different fields and settings for different age categories, and Exhibit 3-2 gives the equivalent productivity curves for what we have called professional experi-

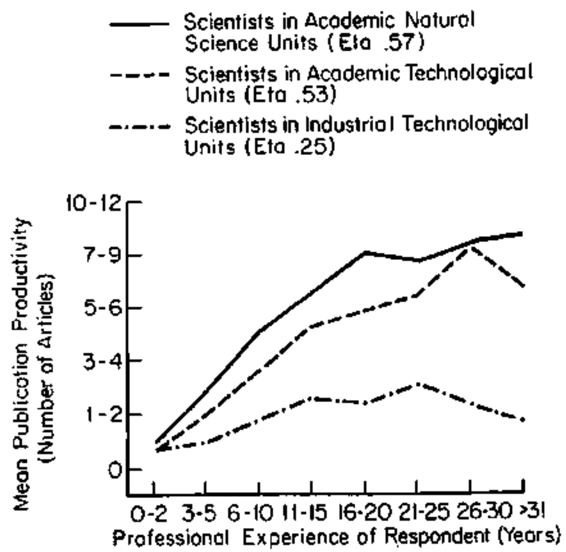


Number of Respondents	29	30-34	35-39	40-44	45-49	50-54	55	
———	506	419	251	152	153	82	119	Total 1682
-----	164	137	79	63	38	40	45	Total 566
-·-·-	114	203	106	78	59	40	34	Total 636

Exhibit 3.1. Mean publication productivity by chronological age for scientists in academic natural and technological sciences and in industrial units.

ence, that is, a scientist's number of years of R & D experience. The latter concept has been introduced in addition to chronological age in order to adjust for the differential disadvantages of those scientists who for various reasons were not continuously involved in scientific work or who started their careers at a somewhat later age. As age and professional experience were highly correlated,[5] productivity curves turned out to have a similar shape for both measures.

When comparing these exhibits, the most interesting difference lies in the fact that the two-peak form of the curve for chronological age, which nicely verifies the results of Pelz and Andrews, tends to change when professional experience is considered. In academic natural science settings, a peak after 15 to 20 years of steadily rising productivity is followed by a period of



Number of Respondents

———	264	423	374	201	155	127	66	68	Total 1678
-----	111	145	104	65	67	36	17	17	Total 562
-·-·-·	88	165	160	87	67	37	13	12	Total 629

Exhibit 3.2. Mean publication productivity by professional age for scientists in academic natural and technological sciences and in industrial units.

stagnation or a very slow rise in the second part of a scientist's career. Scientists working in the technological sciences show a decline in productivity toward the end of their careers, with a very late peak after nearly 30 years of professional work in academic settings and an earlier one after nearly 25 years in industrial research laboratories. In the latter case, the curve is remarkably flatter than in academic settings, implying that age is less related to this kind of productivity in industry. The late peaking of productivity with professional experience of technological scientists in academic settings is mirrored by an early peak when chronological age is considered, suggesting that perhaps a professional career starts earlier in those fields.

Stagnation or decline after a certain period of rising productivity, as more or less confirmed in the present data, has met with

different attempts at explanation in the literature. The most popular interpretation points to the possibility that the more productive scientists may be drawn off into teaching, administration, and other work not productive of scientific output. This is supported in our data, for example, by a positive correlation between age and the number of years the scientist has been head of the research unit, a negative correlation between age and the percent of time spent on research, and a positive correlation between age and the percent of time spent on administration.[6] However, upon closer examination of the age curves for percent of time spent in research and administration, one finds a more or less steady decrease (with research) and steady increase (with administration) of the curves from the very beginning of a professional career almost to the end of it. As an example, Exhibit 3.3 shows the decreasing involvement in research activities with age in all three institutional settings studied in this chapter.

Phrased differently, the results presented so far indicate that publication productivity is *rising* (sharply in academic settings and moderately in industrial settings) for about the first 20 years of a professional career, in spite of the fact that nonresearch tasks are increasing steadily and time in research is *decreasing* continuously during the same time. The most interesting question-somewhat ignored in the literature-is how we explain this more or less steady and continuous rise of productivity for such a long time period, given that (1) scientists are drawn off in work not directly productive of scientific output from the very beginnings of their careers, and (2) it should take only a few years of professional work for a scientist to establish the scientific knowledge and technical competence necessary for scientific publication.

5. Age as a proxy for position in the research laboratory

The fact that scientists are drawn off from research and drawn into administrative and other tasks from the very beginnings of their careers suggests that age-in accordance with our initial thesis-might be considered a proxy for the degree to which scientists occupy various informal and formal supervisory positions.[7] A simple check of such an assumption can be made by asking whether there is any significant direct effect of age and professional experience on productivity, over and above the effect that runs through the position a scientist attains in the research unit. If there were such a direct effect, it could mean that ncreasing age is accompanied by rising technical knowledge and rompetence, and that these could account for the increase in

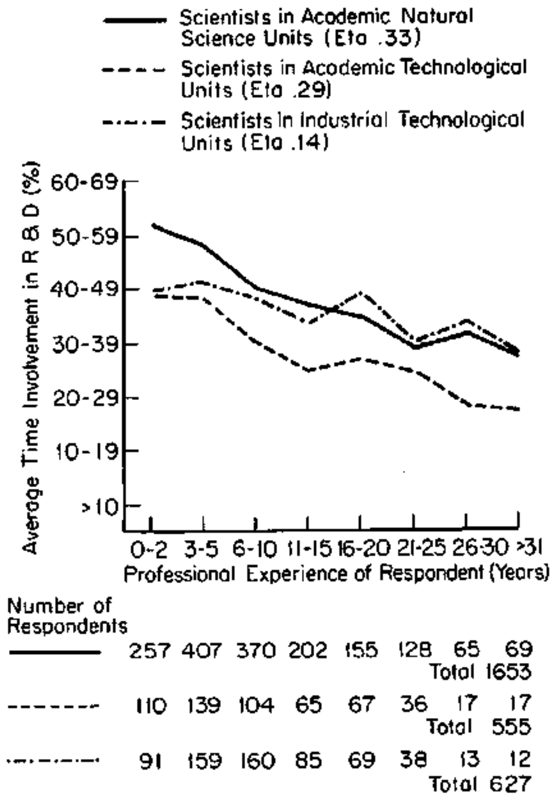


Exhibit 3.3: Mean percentage of time in research by professional experience for scientists in academic natural and technological science units and in industrial units.

productivity, regardless of the position a scientist holds and the task structure and resources that position provides.

By looking at the correlations between age or professional experience and productivity separately for formally acknowledged supervisors like unit heads (which we could differentiate in our data set) and other scientific members of a research unit, including scientists of various supervisory positions below unit heads and nonsupervisory researchers (whom we could not differentiate), the primary importance of position as opposed to sheer age or experience was underlined. For clearly identified supervisory scientists (unit heads), where position was controlled for, the correlation between age/experience and productivity went down and became insignificant, whereas for other scientific

Exhibit 3.4. Pearson *rs* between age/experience and publication productivity for different subgroups of academic scientists

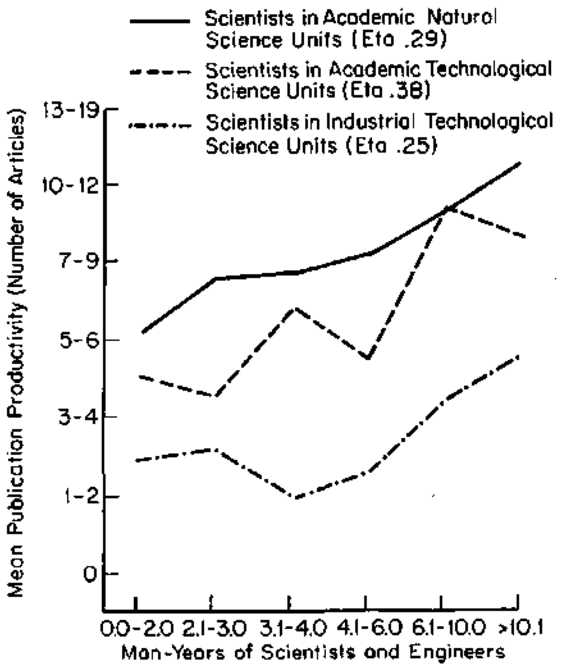
	Pearson rs between productivity and:	
	Chronological age	Professional experience
Unit heads		
natural scientists	.05	.13
technological scientists	.00	.13
Unit members		
natural scientists	.34"	.43"
technological scientists	.32"	*.44"*
Academic natural scientists (all)	.46"	.51"
Academic technological scientists	.43"	.50"

"p « .001.

members (position not controlled for) it remained significant. This implies that position and not age accounts for productivity differences (see Exhibit 3-4).

Another more indirect check of the theoretical priority attribuied to position, for which age stands as a proxy in this analysis, can be made by pointing to the following relationship: If position rather than age were to explain publication differentials, then there should be a positive relationship between a supervisory scientist's access to manpower resources and his or her productivity, for the simple reason that the number of scientists and support staff supervised should act as a multiplying factor as far as the supervisor's quantity of output is concerned. If, however, it were age or professional experience and the presumed rise in personal scientific competence to which increasing numbers of publications per unit of time should be attributed, then there should be no such correlation between a supervisor's manpower resources and his or her productivity.

Again the argument can be checked very simply by looking at the publication productivity of the subgroup of formally acknowledged supervisors, that is, unit heads, for whom the information as to how many scientists, engineers, technicians, etc., they supervised during the last three years (the period of the publication counts) is available; Exhibit 3-5 shows how publication productivity in this subgroup rises with the size of scientific



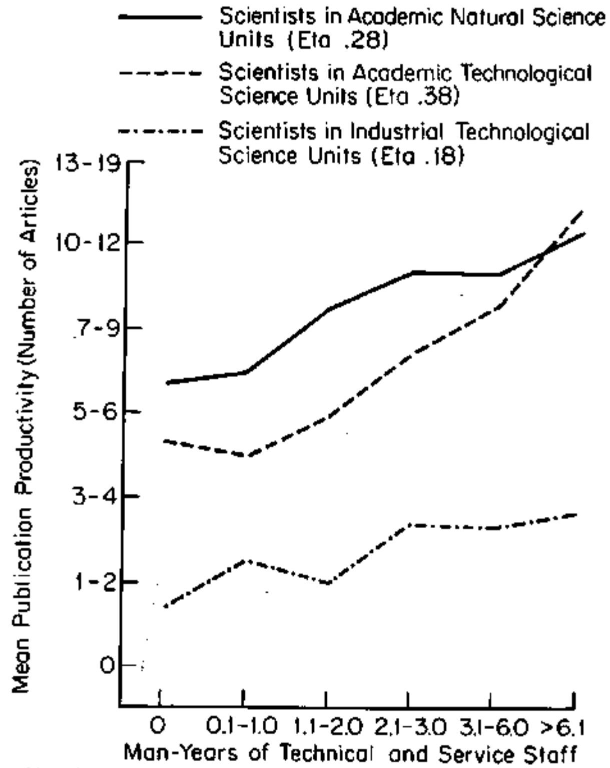
Number of Respondents

———	59	67	68	98	95	57
					Total 444	
- - - -	24	23	35	30	22	22
					Total 156	
-·-·-	55	45	23	27	24	14
					Total 188	

Exhibit 3.5. Mean publication productivity for different manpower resources (scientists and engineers) for supervisory scientists in academic natural and technological science units and in industrial settings.

manpower resources. Exhibit 3.6 documents the equivalent relationship for the size of the technical and service staff supervised.[8]

One can see in Exhibit 3-5 that, as resources in highly qualified manpower increase, there is an almost linear increase in a supervisory scientist's publications in the natural sciences, a two-peaked increase in the technological sciences, and a somewhat less pronounced relationship in industrial settings. Similarly, in both fields and in both kinds of institutions there is a more or less continuous growth of productivity as the size of the technical and service staff supervised by the scientist increases (Exhibit 3.6). Because availability of and access to scientific and technical manpower resources depends on the position a scientist holds in his or her



Number of Respondents

———	92	103	73	57	90	37
					Total 452	
- - - -	28	38	87	17	24	13
					Total 207	
-·-·-	14	44	25	29	31	47
					Total 190	

Exhibit 3.6. Mean publication productivity for different manpower resources (technical and service staff) for supervisory scientists in academic natural and technological science units and in industrial settings.

laboratory, we conclude that the existence of the above significant positive relationship supports our general thesis.

6. Age, task structure, and productivity

If age acts as a proxy for position in the present data, then age should also be related to certain characteristics of the task struc-

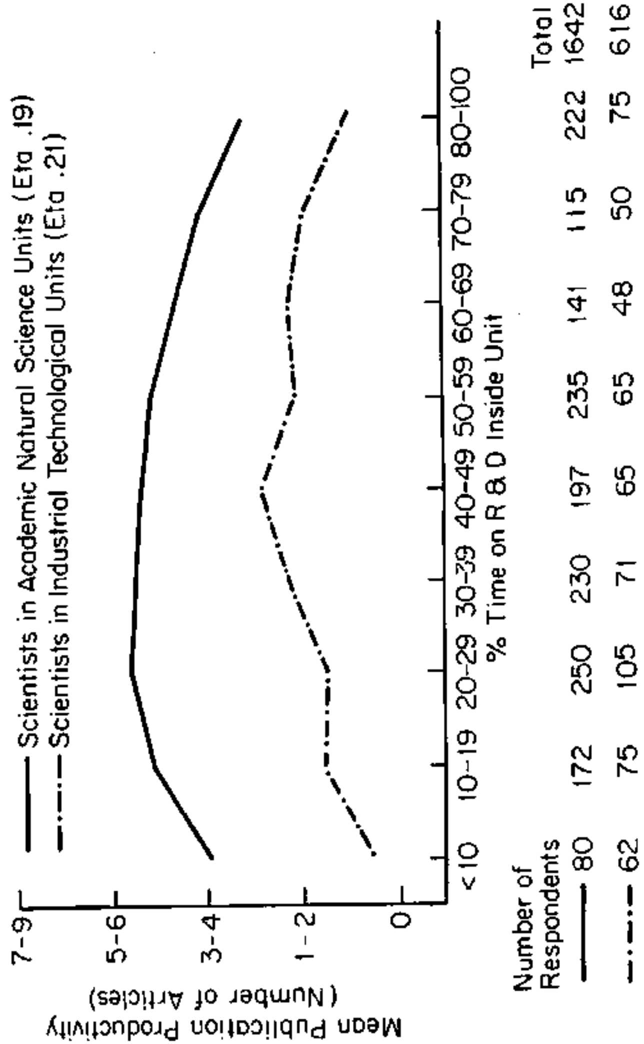


Exhibit 3.7. Mean publication productivity for different time involvements in research for scientists in academic natural science units and in industrial technological science units.

ture associated with supervisory positions. We have already shown that the amount of time in research decreases with age from the very beginning of a career and that involvement in administrative tasks increases steadily. Because productivity also rises continuously, we might suspect that scientists' written productivity does not profit much from sheer time spent in research. Because this seemed somewhat counterintuitive, productivity curves were plotted for different time involvements, controlling as usual for academic field and type of institution. Exhibit 3.7 shows the results for scientists in academic natural science settings and in industrial laboratories involved with technological research. In both cases, the shape of the curve is slightly curvilinear, replicating nicely some of the results in the literature (cf. Pelz and Andrews, 1966): Time involvements lower than 10% *and* around 80% or more are associated with less achievement. In academic settings, publication productivity peaks when about one-third of a scientist's time is spent in research, and it peaks at a somewhat greater time involvement (between 40% and 50%) in industrial units. In sum, however, relationships do not look impressive, as indicated by eta-square coefficients of .04 in both cases.

In order to more specifically address the question of supervisory task structure and its relation to productivity, we controlled for a scientist's position in the unit, assuming that time spent on research might play a more pronounced role in the case of the staff scientists of the unit as compared to unit heads (who in academic settings are often university professors). Exhibit 3.8 shows the resulting productivity curves for both kinds of scientists in academic natural science units. Somewhat unexpectedly, relationships were particularly weak for the staff scientists: Except for the well-known negative effect of extremely little or extremely much research, productivity seemed to be more or less independent of the percent of time spent on development activities within the unit. If it pays for one to be *more* involved with research, then it is the supervisor in the highest position or the head of a unit who reaches a higher level of productivity by spending at least 30% of his or her time on research activities.

If sheer time spent in research does not relate significantly to the publication productivity of a scientist, then it may be the change in the *nature* of involvement in research that is associated with attainment of supervisory positions that accounts for the productivity difference. Devoting relatively small amounts of time to many projects at the early (research conceptualization) and late (report and paper writing) stages clearly offers better

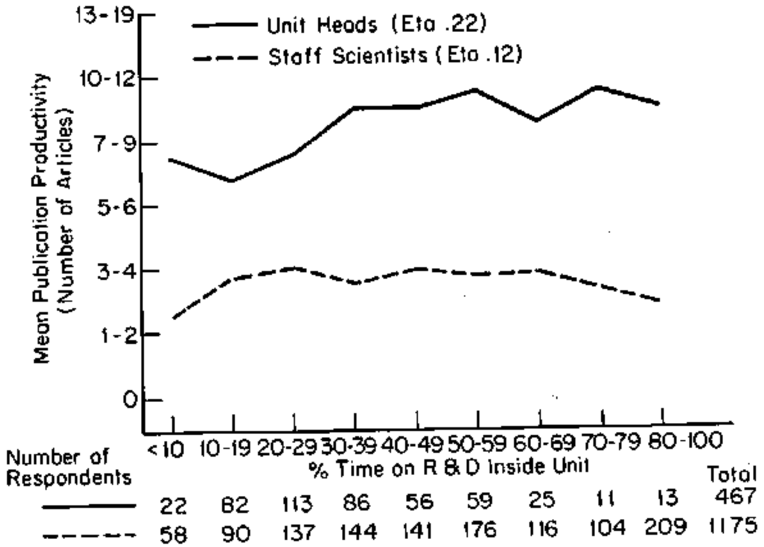


Exhibit 3.8. Mean publication productivity for different time involvements in research for unit heads and staff scientists in academic natural science settings.

opportunities for authorship or co-authorship than devoting large amounts of time to actually doing all the tedious work of one research task. Consequently, if the negative relationship between age or experience and time spent in research, and the lack of a significant correlation between time spent in research and productivity (except for extreme time involvements), can be supplemented by a positive relationship between age/experience and the degree to which the scientist is charged with goal setting rather than executing functions (and if the goal-setting functions are positively related to productivity), this would support our argument that it is the differential advantages associated with supervisory positions that account for much of the productivity differences in research organizations.

To check our argument the following three dimensions have been chosen to represent-to various degrees-a task structure oriented toward goal setting: (1) the diversity of functions of a scientist, an index based on a simple count of every incidence of a greater than 0% time involvement of the scientist in (a) research, (b) teaching, (c) administration, and (d) other scientific activities (like consulting work, scientific documentation, etc.);[9] (2) the degree to which the scientist was involved in setting

research goals for execution by others (like "perception and identification of an area of interest" for the unit) as opposed to genuinely executing the tasks her- or himself (like "collection and production of data" or "literature review");[10] (3) the total number of projects in which a scientist was involved, as an indicator of his or her ability to attract resources in connection with his or her work in the unit.

All three dimensions were thought to mirror the position a scientist held in the unit. The higher the scientist in the hierarchy of the research laboratory, the more he or she would be confronted with a variety of scientific and nonscientific functions in addition to research, the more the nature of his or her involvement would change toward goal setting rather than executing activities, and the more he or she would be able to attract project money and consequently be involved in more projects (as a supervisor or just formally) within and outside the unit.

As can be seen in Exhibit 3-9, which shows correlation coefficients between the above dimensions of task structure, position (as approximated by "professional" age), and productivity, the data substantiate these expectations.

7. A social-position model of publication productivity

We have shown so far that age and professional experience can be used as a kind of proxy for the degree to which a scientist holds a supervisory position,[11] and that the manpower resources and task structure associated with this position relate positively to a scientist's publication productivity. As a final check on our general thesis, we now present a path-analytic model of the presumed structure of relationships as implied so far, ignoring for a moment manpower resources, which were only measured for the unit heads. The fit of the path-analytic model representing this structure has been tested with the help of the Lisrel technique (cf. Joreskog and Van Thillo. 1972; Joreskog, 1974).

The Lisrel technique is a computer program for estimating general linear-structural equation models with the special advantage of allowing for unmeasured hypothetical constructs or latent variables, each of which may be measured by several indicators. The method allows for a differentiation between errors in equations (disturbances) and errors in the observed variables (measurement errors) and yields estimates for both. To check the measurement characteristics that are assumed by Lisrel, a test of linearity of bivariate relationships was made; it showed no significant nonlinearities in the data. All parameters reported in the

Exhibit 3.9. Pearson rs between various dimensions of the research task structure of a scientist, publication productivity, and professional experience, for scientists in academic settings

Dimensions of task structure	Academic natural scientists		Academic technological scientists	
	Years of prof. experience	Publication productivity	Years of prof. experience	Publication productivity
Diversity of functions	.34[a]	.28	.32	.24
Degree of involvement in setting research goals	.40	.42	.38	.34
Number of research projects	.42	.47	.44	.39

[a]For all Pearson rs, $p \leq .001$.

models pertain to standardized variables. Linkages between latent dimensions (circles) represent true relationships[12] and are reported as path coefficients; those between observed (rectangles) and unobserved dimensions represent the construct validity of the measures and are reported as regression coefficients. Other arrows pointing to observed[13] variables indicate the amount of measurement error, whereas those pointing to latent dimensions indicate disturbances or residuals.

As in previous analyses, we chose scientists in academic natural science and technological science units as well as scientists in industrial units as relevant subgroups for replicating the model. Results for academic natural sciences are shown in Exhibit 3.10; for technological sciences in industry, in Exhibit 3.11. The model for academic technological science settings is not included, because results are the same as for natural sciences, with an even higher amount of variance explained.[14]

The ability of Lisrel to reproduce the input correlations among observed variables was generally good: The mean deviation of the estimated correlations from the observed correlations in the model of Exhibit 3.10 was .025, and in Exhibit 3.11, .024; the highest discrepancies were .134 and .161, respectively.

The good fit of the model supports the presumed structure of relationships: A scientist's age (used as a proxy for the degree to which he or she holds a supervisory position) is related to his or her task structure in the research laboratory, and this in turn is related to his or her publication productivity.

Because the Lisrel method allows for multiple indicators (shown by the rectangles in Exhibits 3.10 and 3.11) of each concept (shown by the circles), age is assessed by both chronological age and professional experience. Similarly, supervisory task structure, as described above is represented by three dimensions: the diversity of functions, the volume of goal-setting research functions, and the number of projects in which the scientist was involved.[15]

When screening the data to detect other potential organizational effects upon individual publication productivity, no further variables were significantly related to an individual scientist's output in academic settings. It is important to note that the five-variable pattern of relationships that identifies supervisory position as the major explanatory concept relating to intraorganizational productivity differences seemingly dominates all other bivariate relationships between organizational variables and publication productivity as emerging from correlation analyses.[16]

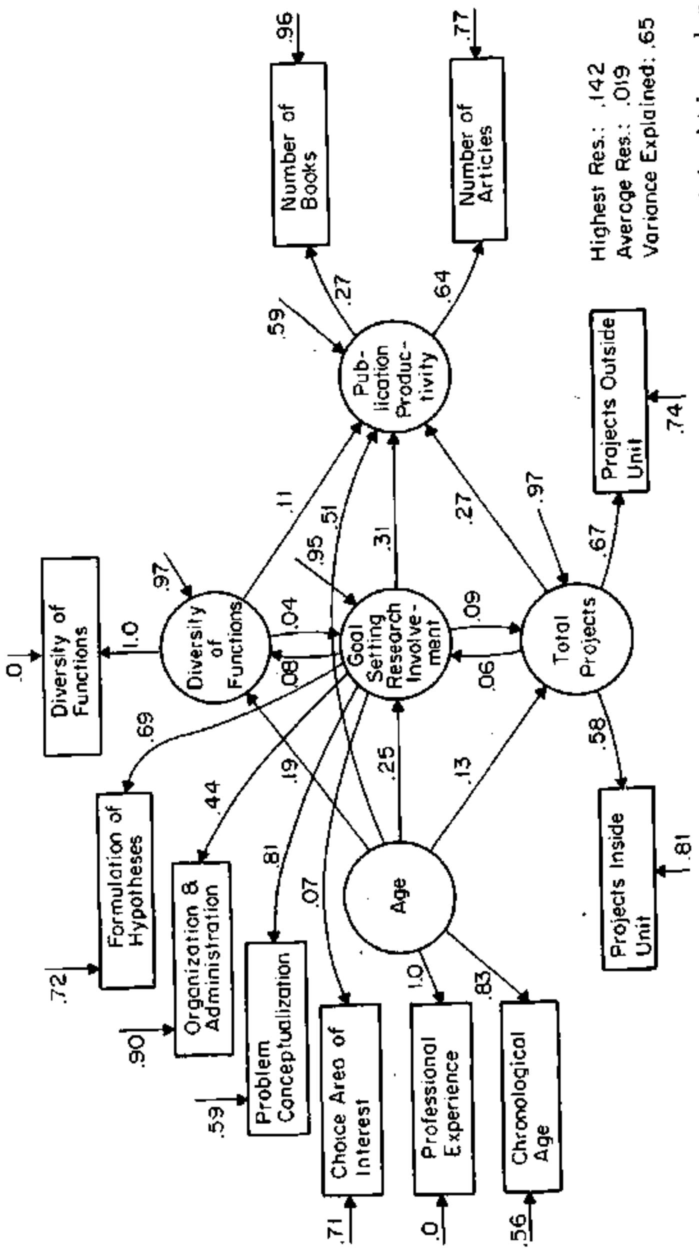


Exhibit 3.12. Lisrel model of individual publication productivity for staff scientists (i.e., excluding unit heads) in academic natural science settings.

8. Control for a scientist's position

As can be seen from an inspection of the models presented so far, there remains a relatively high direct effect of age and professional experience on publication productivity in academic settings.[17] We have already shown that the relationship between age/experience and productivity tends to disappear when a scientist's supervisory position is controlled for (see our discussion of Exhibit 3.4). In order to check the validity of our previous argument in the case of the multivariate relationships we are now confronted with, we estimated the social-position model of individual publication productivity in academic natural science settings separately for supervisory scientists (unit heads) and unit members. In accordance with what we have said so far, the model would be expected to replicate nicely for unit members (because this subgroup includes various kinds of supervisory positions below unit heads), but should, being a social-position model, change significantly when unit heads are looked at exclusively.

Exhibits 3.12 and 3.13 substantiate these expectations: In the case of scientific members of a unit (Exhibit 3.12), the model maintains its significance, with only slight changes in the parameters linking concepts, and an explained variance in productivity of 65% (as compared to an original 67%). In the case of unit heads (Exhibit 3-13), the variable "quantity of manpower resources at the head's disposal" (which was not measured for unit members) was included in the model. This latter variable yields the highest path coefficient, followed by the variable "number of projects" (the supervisor is involved in). This suggests that once a supervisory position is attained, *manpower resources* and *project tasks* account for much of the variance in *further* productivity differences. In accordance with this, the direct relationship between age/experience and productivity is reduced to .03 (from .45 in the global model!), clearly indicating that there is no remaining effect of age once position and what it stands for are taken into account.

9. Technological scientists in industrial research units

From an inspection of Exhibits 3-10 and 3-11, it can be seen that both models in general show good fit, as assessed by highest and average residuals, yet the amount of variance explained in individual productivity varies greatly between the two types of institutions involved: There is a decrease of 30 percentage points between the variance explained with the model for scientists in

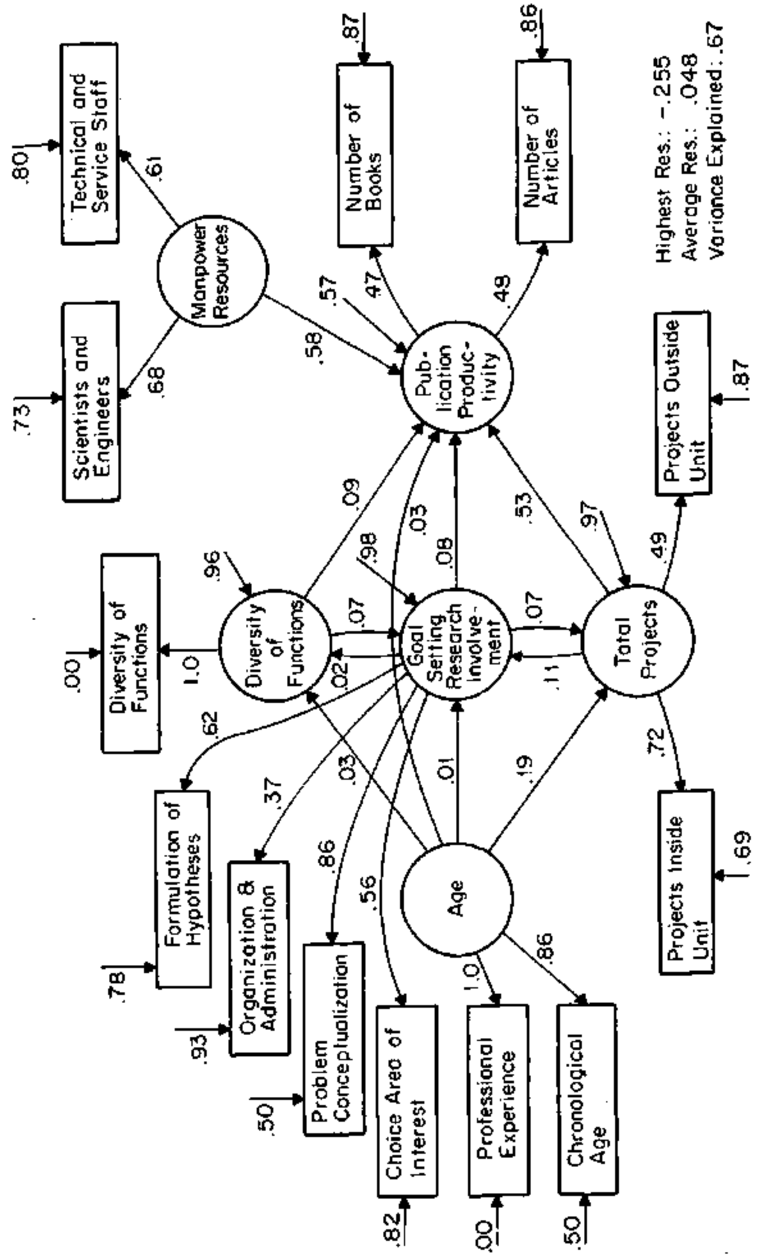


Exhibit 3.13. Lisrel model of individual publication productivity for supervisory scientists (unit heads) in academic natural science settings.

academic natural science settings (67%) and for scientists in industrial firms (37%).[18]

The smaller amount of variance explained in industrial settings by the social-position model of publication productivity suggests that there might be other factors specific to industry that should be taken into account. Exhibit 3.14 presents a model that includes two principal other sources of explanation, one referring to influences on the *choice of the research theme* of an industrial laboratory, the other referring to the amount *oiexternal communication*[19] the unit maintains.

The first source subdivides into two different factors relevant to enhancing productivity: the degree to which scientific significance is taken into account when the research tasks of a laboratory are being determined, and the degree to which science policymaking bodies determine the choice of research tasks (as in socialized industry). Whereas the first factor seemingly points to an industrial research unit's orientation toward basic research, which is itself linked to external communication and to more emphasis on publications, the second factor could imply a certain policy of legitimizing public (governmental) money spent on research by pressure toward publishing all the results obtained. Both factors refer to characteristics of the organizational context in which a scientist is working. It is plausible to assume that this context is especially important for enhancing or restricting publication productivity in industry because: (1) Scientists in industry are generally operating under more organizational constraints than in academic settings; and (2) publications are not a typical form of industrial research output and hence will flourish only under special conditions.

The expanded model is shown in Exhibit 3.14. Reproduction of observed correlations by parameters produced by the Lisrel program was good again: The average discrepancy between observed and fitted correlations was .033; the highest discrepancy was .161. The model now accounts for somewhat more than half the variance in individual publication productivity in this setting (53%). A gain of 16 percentage points resulted from adding organizational context variables to the individual position effects of the former model in Exhibit 3.11.

10. Group productivity and its correlates

Having outlined the position of a scientist and the manpower resources and supervisory task structure associated with it as the major explanatory factor in accounting for the productivity dif-

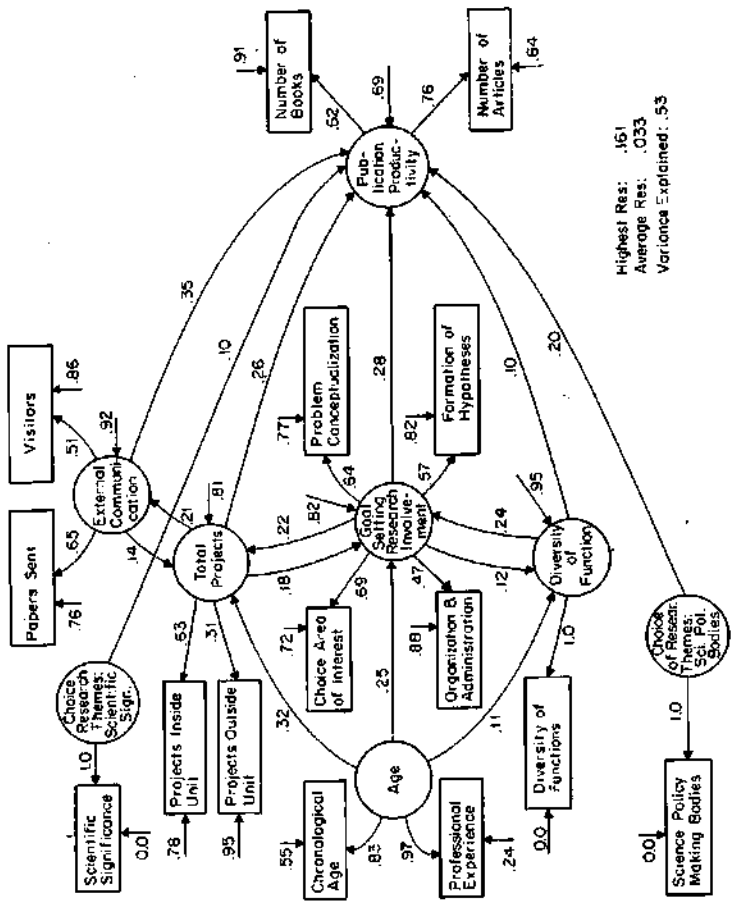


Exhibit 3.14. Lisrel model of individual publication productivity including choice of research themes, for technological scientists in industry.

ferences of scientists, we were interested to explore whether group publication productivity can be explained by individual members' productivity or whether the analysis would have to incorporate additional factors.

Group publication productivity can be introduced here as a measure of the quantity of papers published in scientific journals by the members of a research unit during the last three years in connection with the work of the unit (we shall also consider the publication of books). Group productivity defined this way is not identical with the sum of publications reported by group members during that period, nor with mean productivity as defined by the sum divided by the number of persons in the group. The quantity of group publications differs from the sum of individual members' publications in that (1) the effect of multi-authorship has been eliminated,[20] and (2) the *aggregate* character of the concept assures that individual productivity differentials are wiped out in the group measure.

Seen this way, the quantity of publications should be a more valid indicator of the group's overall contribution to science than the sum of individual publication productivities (because it is the number of actual products that is counted). Furthermore, group productivity scores might allow for a better exploration of context (organizational) effects than would individual productivities (and their possibly more personality-linked origins).

Before attempting to account for group productivity, let us show how productivity scores of supervisory scientists (unit heads) and scientific members of the unit relate to group productivity. Because many of the results in the literature refer to departmental prestige in relation to quantitative productivity, Exhibit 3.15 includes a measure of the recognition[21] received by the research unit in order to check for its association with quantitative output.

In accordance with the analysis presented so far, there is a dominant relationship of supervisory productivity over group productivity. Exhibit 3.15 shows that, on the average, supervisory productivity accounts for three to five times more variance in group productivity than does the output of the research members of the group in academic settings. In industrial settings, this ratio is somewhat lower, but there are still pronounced effects of the supervisor, especially as far as articles abroad and books are concerned. The same holds for departmental prestige as measured by the recognition the unit receives by the scientific community: Here too the correlations are higher for supervisory scientists than for scientific members of the unit.

Exhibit 3.15. Pearson *r*s between publication productivity scores of individual scientists of a unit and group productivity scores of the unit for different measures of productivity

	Group productivity measure							
	Articles publ. in country		Articles publ. abroad		Articles and books		Recognition of unit	
Publication productivity of:	r	r^2	r	r^2	r	r^2	r	r^2
Academic natural scientists:								
unit heads	.39	.15	.48	.23	.62	.38	.44	.19
unit members	.26	.07	.19	.04	.29	.08	.26	.07
Academic technological scientists:								
unit heads	.61	.40	.43	.18	.68	.46	.39	.15
unit members	.39	.15	.18	.03	.34	.12	.19	.03
Industrial technological scientists:								
unit heads	.60	.36	.36	.13	.68	.46	.44	.19
unit members	.50	.25	.23	.05	.38	.14	.32	.10

Exhibit 3-16. Predictive power of several variables in explaining group publication productivity

	Academic natural science groups (N = 450)		Academic tech. science groups (N = 154)		Industrial tech. science groups (N = 180)	
Predictor variable	Beta	Eta^2	Beta	Eta^2	Beta	Eta^2
Group head's publication productivity	.47	.38	.49	.46	.52	.40
Staff scientists' publ. productivity	.23	.19	.24	.23	.17	.16
Size of research unit	.22	.17	.29	.26	.31	.15
Scientific exchanges of group	.14	.15	.24	.22	.15	.13
Age of research unit	.12	.08	.14	.11	.16	.03
Multiple R^2 unadjusted	.54		.64		.54	
Multiple R^2 adjusted	.50		.59		.44	

Note: Results are from multiple classification analysis.

The existence and size of the above correlations already suggest that individual publication productivity accounts for a substantial amount of variance (varying according to individual position) in group productivity. When exploring different *organizational* characteristics by means of multiple classification analysis[22] in a further attempt to explain group productivity, we found that the following three variables-in addition to individual productivity-seemed to influence the published output of a group: the *size* of the research units, as measured by the average number of man-years of scientists and engineers working in the group during the last three years; the *age* of the unit, as measured by the number of years the unit has existed formally under its present name and goal structure; and the *scientific exchange* maintained by the unit by exchanging publications with other groups or individual scientists working in the field. Exhibit 3.16 lists the beta and eta-square parameters[23] as well as the multiple correlation coefficients for this set of predictors for academic groups in natural and technological sciences and for industrial groups in technological sciences.[24]

Exhibit 3-16 confirms that the supervisors' productivity can account for most of the variance in group productivity in all subgroups, followed by either group members' productivity or unit size. Scientific exchanges and age contribute less to overall explanatory power. The relationships of head's and members' productivity, of size, and of scientific exchanges to group productivity are all positive and tend to be monotonic.

Generally, one could say that although the variables listed above account for a reasonable amount of variance in the dependent measure, they do not contribute significantly to our understanding of mechanisms associated with group productivity. That the size of a research team should be related to the number of articles it produces comes as no surprise, and it would have been a serious blow to our confidence in the results if individual productivity had not come up as a major contributor to group productivity. The same holds true for the scientific exchanges of a group: High publication productivity in most cases will be associated with more activities in sending out and receiving papers, and this may be a result much more than a cause of the quantity of output of a group. The least clearcut and least easily predicted relationship is that with unit age; however, unit age seems to contribute only marginally to explaining group productivity.

In order to check the above results and to improve our understanding, it seemed essential to adjust the number of group publications for the average size of the group during the last three years[25] and then to try and predict the resulting per capita publication productivity of the group using the same and other variables. Although relationships between per capita productivity and the variables above were maintained but did change in size and form, it is interesting to note that no other variables were identified as substantially contributing to the explanation of group productivity when bivariate relationships were examined.

Exhibit 3.17 presents the results of the multiple classification analysis on. the above input variables when per capita productivity measures are used as the dependent variable.

By comparing the beta and eta-square coefficients of Exhibit 3.17 with those of Exhibit 3-16, it can be seen that the contributions of the head's and members' productivity to group productivity remain about the same in academic units and tend to be somewhat higher in industrial settings;[26] similarly, the relationship between scientific exchanges and group productivity remains positive and is sometimes more pronounced than with total productivity scores. Additionally, unit age again contributes only marginally to the overall variance explained.[27] The most interesting result clearly pertains to the relationship between *group size* and adjusted productivity scores. Exhibit 3-18 presents the raw and adjusted[28] means of per capita publications for groups of different sizes in academic and industrial settings; it shows that size is *negatively* related to per capita productivity in natural sci-

Exhibit 3-17. Predictive power of several variables in explaining per capita group publication productivity

	Academic natural science groups (N == 456)		Academic tech. science groups (N == 157)		Industrial tech. science groups (N = 175)	
Predictor variable	Beta	Eta^2	Beta	Eta^2	Beta	Eta^2
Group head's publication productivity	.45	.23	*.46*	.33	.59	.49
Staff scientists' publ. productivity	.27	.16	*.26*	.16	.28	.24
Size of research unit	.46	.16	.36	.14	.15	.09
Scientific exchanges of group	.17	.10	.22	.14	.22	.18
Age of research unit	.11	.02	.16	.09	.19	.05
Multiple R^2 unadjusted	.55		.54		.65	
Multiple i?^{z} adjusted	.51		.42		.57	

Note: Results are from multiple classification analysis.

Exhibit 3.18. Raw and adjusted means of per capita group productivity (number of articles) by group size in natural and technological sciences

Group size (average scientific man-years)	Academic natural science groups (N '= 456)		Academic technological science groups (N - 157)		Technological science groups in industry (N == 175)	
	raw	adjusted	raw	adjusted	raw	adjusted
0 - 2.0	3.8	4.3	*2.6*	3.3	1.6	1.8
2.1- 3.0	3.9	4.3	3.0	3.7	1.7	1.7
3.1- 4.0	4.0	4.2	3.4	3.3	1.3	1.4
4.1- 6.0	3-5	3.5	2.6	2.7	1.8	1.7
6.1-10.0	3-8	3.4	3.8	2.9	1.7	1.2
>1 0.0	3.2	2.7	3.0	2.5	2.3	2.5
Eta	.40		.37		.29	
Eta^2	.16		.14		.09	

Note: Results are from multiple classification analysis.

ence groups, and that the raw relationships, which tend to be positive in technological sciences, become negative when the effects of other variables are controlled and one looks at adjusted means.

A number of studies have appeared on the effect of organizational size, with inconsistent findings. Whereas Meltzerand Salter (1962), for instance, report that size remained totally insignificant in explaining the productivity of physiologists, Wallmark and associates (Wallmark and Sellerberg, 1966; Wallmark et al., 1973) claim that the efficiency of research teams increases exponentially with the size of the team. However, both authors use definitions of the "team" or "unit" that are not comparable to our case.[29] Hagstrom (1971) presents an argument in favor of a positive effect of size by saying that size permits breadth to be combined with that specialization that is necessary for rapidly developing research fronts. Furthermore, one could argue that if innovations occur randomly in a speciality field, then the likelihood of this phenomenon would be greater in larger units. Similarly, if productivity depends on the availability of substantial resources and is linked to high-status scientists (cf. Mullins, 1975), then again larger groups should provide more chances of fulfilling this requirement. On the other hand, according to Worthy's (1950) well-known theory, larger size is accompanied by a proliferation of hierarchical levels and institutionalized relationships that prevent the exploration of an individual's full capability and lead to low morale and output. We might add that scientific field and the associated technology requirements could play a key role in determining optimal group size, as suggested by the far less pronounced negative effect of size in technological science research units and especially in industry in our data. Blume and Sinclair (1973a,b), for instance, found that the relationship between size and productivity varies considerably between areas of a single discipline (chemistry). They speculate on the multiplicity of skills required for some types of research and on the degree of "mechanization" and typification of the research procedure as influencing this relationship. Whereas considerations such as these might be relevant for explaining the differential importance of size in natural and technological science disciplines, the results are not directly applicable to the present analysis because measures of individual publication productivity are considered. Finally, we should point to results by Stankiewicz (1976) on the present data set, which show that the relationship between group size and productivity in academic settings varies in different countries, suggesting that differing organizational structures of the university

system (e.g., is size associated with a flat type of structure or highly correlated with the number of levels in the organization?) will have to be taken onto account when analyzing the problem.[30]

Summarizing our results on group productivity, we might say that there are two major results worth noting: (1) Individual publication productivity emerges as the major explanatory variable of group per capita output (which means that we are referred back to our individual publication models); and (2) the size of the group tends to relate negatively to per capita productivity (varying in degree according to field and institution) in the six-country data set.

11. Discussion

Some of the limitations of the preceding analysis can be made apparent by pointing to two different interpretations that can be associated with what we have documented: that individual productivity when analyzed in terms of organizational variables is mainly accounted for by the social position the scientist holds in the scientific hierarchy of his organization. One interpretation (put forward by us so far) would attribute differences in publication rates to the operation of the stratification system inside organizations. Advancement on the (formal or informal) hierarchy is associated with differential access to resources and with differences in functions and involvement in research, which in turn leads to a higher probability of authorship or co-authorship for the scientist. This hypothesis suggests that the status of a scientist significantly affects the quantity of publications he or she can claim, irrespective of his or her personal innovativeness and productivity. The second interpretation would describe differential productivity associated with position as an outcome of the differential capability and technical competence of a scientist, deriving the higher productivity of higher-position scientists from a movement of more capable and higher-perform ing researchers into supervisory positions.

The two interpretations do not necessarily contradict each other. If early publication productivity based on personal capacity and dynamic orientation[31] leads to promotion into supervisory status, then resources and functions conducive to producing output might replace or strongly reinforce original capacities. The last-mentioned effects are verified in the present data by the significant increase of supervisory productivity obtained with an increase in the size of the scientific and technical staff supervised: It will be remembered that staff size and volume of projects together account for almost all the variance of the unit head's publications in the Lisrel model.

The present data do not permit a check of original productivity capacities. They do, however, call into question the argument that a scientist's productivity suffers as he or she takes on supervisory duties that involve higher percentages of nonresearch tasks and hence keep him or her from pursuing research work. Except for the rare cases where a scientist leaves the scientific hierarchy, he or she seems to be not drawn off, but rather drawn *into* publication productiveness by advancement in the hierarchy, whatever his or her original production capacities may have been.

These results can be used to shed new light on the meaning of productivity as measured by publication counts and on some of the earlier findings relating to it.[32] If what is measured is authorship rather than talent for creating research results, and if-as pointed out by Crane[33]-the norms in some fields allow supervisors to claim authorship for the work of students or staff scientists whereas the norms of other fields do not permit this, then it may be more appropriate to attribute productivity to the privileges of higher rank and to supervisory efficiency in productively organizing the task force than to seek explanations in terms of factors enhancing individual production capacities. Consequently, switching the attention from the notion of (publication) productivity as used in the literature to the notion of authorship as emerging from the present analysis may pave the way for a better understanding of science as a highly stratified and elitist system and of the impact this has on the development of scientific knowledge.

12. Summary

Studies of stratification in science have increasingly accepted the idea that science is a highly stratified and elitist system with skewed distributions of productivity and rewards. Attempts to explain the higher productivity of higher-status scientists by pointing to the greater ease with which their work might be accepted by journals and publishers were not supported by the data in some recent studies. If status in general does not confer greater ease of publication, this chapter argues that position within a research organization does confer greater ease of author- or co-authorship, and that this is the major explanatory variable accounting for productivity differences within research laboratories as far as quantity of articles (and books) is concerned. Upward moves in a laboratory's formal or informal hierarchy are associated with a change in a scientist's research involvement from goal-executing to goal-setting functions as well as with an increase in access to scientific manpower and project money. Having goal-setting tasks permits a significant reduction in the time expenditures in research necessary to assure that the scientist is identified with the research results and, hence, permits involvement in more research tasks than originally. Equivalently, resources in scientific manpower and project money act as multiplying elements as far as quantity of output is concerned. When group productivity is considered, individual publication productivity and especially supervisory productivity retain a major significance. Additionally, the size of the research unit seemingly plays a key role: In the present data set, size tends to be negatively related to per capita group productivity, with the most pronounced relationships occurring in academic natural science units.

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Notes

1. The technological sciences as defined by the Unesco nomenclature basically comprise all applied branches of natural science disciplines (such as chemical technology and engineering or nuclear technology), in addition to such inherently technological fields as motor vehicle technology or materials technology.

2. To cite but a few examples, Blume and Sinclair obtained a Goodman-Kruskal correlation coefficient of .63 between peer group assessment of the work of a scientist and number of published papers; Cole (1967) found a Pearson correlation of .60 between citation and paper count and a correlation of .72 between number of papers and number of citations to the three most frequently cited contributions of the scientist (a measure that cannot be an artifact of the quantity of publications); and Pelz and Andrews (1966) report a

Pearson correlation coefficient near .40 between ratings of a scientist's contribution to technical or scientific knowledge in the field by members of the same laboratory and number of papers published in professional journals within the past five years.

3. The quality of scientific work of a researcher was measured by peer and supervisory ratings of his group from within and outside the unit on several dimensions. See Chapter 2.

4. The average correlation between output of papers and of books for unit heads and staff scientists in academic science and industrial research units is .25. As expected, publication measures were highly skewed in that only a small number of scientists proved to be highly productive, whereas most scientists either had not produced at all or reported only very few papers; accordingly, publication measures were grouped before further use to reduce skewness.

5. The Pearson rs between age and professional experience for academic natural scientists, and for technological scientists in academic settings and in industrial settings, are .85, .83, and .76, respectively.

6. The correlations (Pearson rs) are, respectively, .47. -.36, and .44 in academic natural science settings; .36, -.34, and .37 in academic technological science settings; and .39, -.14, and .26 in industrial technological science settings.

7. Examples of such positions might be supervising the work of technicians and graduate students, directing-instead of participating in-projects, and heading a laboratory.

8. Manpower resources in both cases are measured in terms of the average number of man years of (1) scientists and engineers (Exhibit 3.5), and (2) technical and support staff (Exhibit 3.6) in the unit supervised by the scientist during the last three years.

9. The range of the index accordingly varies from 1 to 4; the index is based on a general question as to how much of the total work time of the scientist this year was devoted to the above categories, additionally including "routine and control analyses," "design and engineering studies," and "other professional functions" under category (d) above.

10. Indicators used to measure the volume of goal-setting functions are the following: degree of involvement in "perception and identification of an area of interest," in "problem precision: conceptualization, formulation, analysis," in "time-table, administration, organization and economic considerations," and in "formulation and statement of hypotheses"; all items were measured on five-point Likert scales.

11. More specifically, one should say that age and experience act as a proxy for position in relation to publication productivity because there seems to be no direct effect of age over and above what is explained by a scientist's supervisory position. However, that age should be associated with position to such a degree in academic settings is in itself interesting, and points to the fact that advancement in academic bureaucracies is based upon the principle of seniority.

12. To ensure the identifiabiJity of the model, the parameters associated with the symmetric linkages between the unobserved dimensions of functions and tasks performed by the scientist were constrained to be equal.

13. When there was only one observed indicator for a latent dimension (e.g., diversity of functions), the linkage between the two was fixed at 1.0 and the measurement error in the observed indicator was assumed to be zero.

14. The highest residual in this case is .191, the average residual .032, and the amount of variance explained is 81%.

15. Positive relationships between these dimensions and the voluntary overtime a scientist devotes to his or her work and his or her attachment to the research unit can be shown (for example, Pearson rs between the age of a scientist and his or her attachment to the unit are .36 for academic natural scientists and *.24* for scientists in industry), but were left out of the model because they contributed practically nil to explaining publication productivity when other concepts were included.

16. The final version of the model has been checked with the help of the Goodman technique (Goodman, 1972a, 1972b, 1973), which has the advantages of not requiring any of the assumptions of linear regression to be met by the data and of allowing for an explicit inclusion of interaction effects. Results confirmed thar there are no significant interactions or nonlincariries in the variables; furthermore, the model showed an excellent fit, in accordance with what we would expect from the Lisrel results (see Waller, 1976).

The model for scientists in academic natural science units has further been replicated for all six countries individually. The fundamental relationship between age and publication productivity held in all instances. The major discrepancies were that the diversity of functions related negatively to publication productivity for Finland and that the amount of variance transmitted via the number of projects differed. In Belgium, a high correlation between age and projects was found, whereas Austria was on the other side of the spectrum, showing a high direct correlation between age and publication productivity but only a small one between age and projects.

17. This is indicated by a parameter of .45 in the Lisrel model of academic natural scientists (see Exhibit 3.10) and by a parameter of .36 for academic technological scientists (model not included). It is worthwhile noting that this direct effect disappears in industrial settings and hence the linkage has been eliminated in the final model (see Exhibits 3.11 and 3.14).

18. Parameter estimates differ between the models most markedly with respect to the total number of projects (which seems more important in the technological sciences than in the natural sciences) and with respect to the direct linkage between age and publication productivity (which practically disappears in industrial research units).

19. Two indicators have been chosen as measures of external scientific communication: the number of visiting scientists from the country who had visited the unit during the past year, and the number of publications of the unit sent to other individuals or organizations in the field. Several other indicators could also be used here, e.g., the number of scientists from abroad or the number of publications received by the unit (cf. Knorr et al., 1976). It must be noted, however, that the number of publications sent to other groups might be a result rather than a cause of publication productivity; the same holds-to a less obvious degree-for all indicators of external contacts. This points to the hypothetical character of the causal links specified, which should be kept in mind when interpreting the models.

20.. With group publications, it is the number of papers that is counted and not the number of authors, as would be the case if publications reported by group members were added together.

21. Recognition has been measured by aggregating responses of unit members as to the degree to which the unit has a high international reputation and the degree to which publications of the unit are in high demand and often cited in the literature. The index was built by combining the scores of the unit heads and mean scores of staff scientists. (Chapter 2 provides further details.)

22. Multiple classification analysis is a multivariate technique for examining the raw, adjusted, and multiple effects of several predictor variables on a dependent variable based on an additive model. Unlike traditional regression analysis, the technique can handle predictors with no better than nominal measurement and with nonlinear interrelationships, but cannot handle (directly) interaction effects (see Andrews et al., 1973).

23. Betas are analogous to standardized regression coefficients; see Andrews et al. (1973: 47 ff.) for full discussion. "Eta-square" is the correlation ratio and indicates the proportion of the total variance in the dependent variable that is explainable by the predictor.

24. These and the following analyses refer to the *research unit* as the unit of analysis to which the variables size, age, and scientific exchange pertain; group members' publication productivity is calculated as the average of the productivities of the unit's staff scientists; the unit head's publication productivity was scored separately.

25. This was done by dividing the number of articles in the unit during the last three years by the average number of man-years of scientists and engineers in the same period.

26. The result that the multiple classification analysis explains only about half the variance of per capita group publication productivity, in spite of the inclusion of individual group members' publication productivity among the predictor variables, is related to the fact that the group measure refers to the number of products *in the group,* whereas the measure of individual publication productivity refers to total authorships.

27. It should be noted, however, that the form of the relationship in industrial settings changes from a negative to a curvilinear relationship.

28. The adjusted means control for the effects of individual publication productivity (heads' and members' productivity), unit age, and scientific exchanges.

29- Additionally, Wallmark et al.'s definition of team size as the number of authors from a given organization seems to be correlated with their productivity measure.

30. See also Chapter 8.

31. Meltzer (1949) showed a negative association between age at first publication and career productivity and points to the general proposition that the best predictor of an activity is a specimen of past performance in the activity.

32. The results of Blume and Sinclair (1973b), which show that higher-ranking scientists are more productive in larger groups and that the relationship between group size and individual productivity varies between specialities, can for instance be reinterpreted as showing the advantages higher-rank scientists gain from staff size. Equivalently, the results can be held to confirm the relevance of norms specific to single fields in establishing higher-rank privileges.

33. Comment on this chapter.